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# TOXIC CHOICES: THE THEORY AND IMPACT OF SMOKING BANS*

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**ABSTRACT**

Smoking bans in the workplace and public places are now ubiquitous. While indices of such controls are commonly included in econometric models, there exists little theory that validates or analyzes them. This paper first proposes a theoretical model of maximizing behaviour on the part of smokers which serves as a vehicle to evaluate bans. It is a type of nicotine inventory management model where smoking during one phase of the day impacts utility in other periods. It also includes an intensity choice as part of the optimization. Calibrated model simulations suggest that, with the exception of heavy smokers, workplace bans have relatively minor impacts on smokers throughout most of the distribution due to substitution possibilities. We estimate quantile regressions using Canadian survey data for 2003 and .find that workplace bans have a surprisingly small impact on the number of cigarettes smoked. However, restrictions on smoking in the home are found to be of an order of importance greater, even when instrumented. The policy conclusion is that the effectiveness of workplace bans depends heavily upon whether there exist complementary restrictions on smoking in environments to which individuals may wish to switch their smoking following a workplace ban.

**JEL Classification:** H21, I12
**Key words:** Smoking bans, tobacco, nicotine, cotinine, intensity, quantile regression

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# Toxic Choices: The Theory and Impact of Smoking Bans*


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Smoking bans in the workplace and public places are now ubiquitous. While indices of such controls are commonly included in econometric models, there exists little theory that validates or analyzes them. This paper first proposes a theoretical model of maximizing behaviour on the part of smokers which serves as a vehicle to evaluate bans. It is a type of nicotine inventory management model where smoking during one phase of the day impacts utility in other periods. It also includes an intensity choice as part of the optimization. Calibrated model simulations suggest that, with the exception of heavy smokers, workplace bans have relatively minor impacts on smokers throughout most of the distribution due to substitution possibilities. We estimate quantile regressions using Canadian survey data for 2003 and find that workplace bans have a surprisingly small impact on the number of cigarettes smoked. However, restrictions on smoking in the home are found to be of an order of importance greater, even when instrumented. The policy conclusion is that the effectiveness of workplace bans depends heavily upon whether there exist complementary restrictions on smoking in environments to which individuals may wish to switch their smoking following a workplace ban.



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# 1 Introduction

The purpose of this paper is to formalize theoretically and evaluate empirically the effectiveness of smoking bans or restrictions both in the workplace and the home. A substantive empirical literature now documents the quantitative impact of workplace smoking bans, and many empirical papers that estimate the impact of tax/price measures attempt to control for the impact of bans, broadly defined. Evans, Farrelly and Montgomery (1998) has been particularly influential because it controlled for the possible endogeneity of the choice of work place. While there is a concensus at the present time that workplace bans reduce smoking, there has been very little by way of theoretical support for such findings. In particular, why do smokers not substitute heavily in their smoking to periods of the day where smoking is not restricted?

Furthermore, if smokers do reduce the number of cigarettes they smoke as a result of restrictions on their behavior, are they likely to smoke in a more intensive manner? Higher intensity means that smokers take longer, deeper and more frequent puffs. It has long been recognized in the toxicology literature (e.g. Jarvis *et al*, 2001a) that the quantity of cotinine in a smoker's saliva or bloodstream is only loosely correlated with the number of cigarettes smoked or indeed the strength of cigarettes smoked; 'strength' denoting where in the spectrum between 'light' and 'regular' that a particular cigarette brand is located. Regular strength cigarettes have the potential to deliver more nicotine and other pleasure yielding toxins than lighter brands. Evans and Farrelly (1998) proposed that higher per unit taxes induce smokers to switch from light to regular, and Harris (1980) recommended a tax based upon nicotine content. More recently, Adda and Cornaglia (2006) have observed that the amount of cotinine in a smoker's body increases only weakly with the number of cigarettes smoked; indicating a strong degree of intensity substitution in response to changes in the number of cigarettes smoked, that might in turn be induced by policy measures designed to restrain smoking.

The first objective of this paper is to develop a theoretical model of choice on the part of a smoker who faces three choices: how many cigarettes to smoke, at what intensity to smoke them, and at what intervals during the day. Having developed a model that involves these tradeoffs we impose time restrictions on smokers that limit when they can smoke. In order to maximize their utility, smokers must choose a new triple. We solve this problem using numerical methods, having parameterized the model in such a way that it mimics observed behaviors. In essence this is a type of rationing problem. But while the theory underlying the rationing of 'goods' is well developed (Tobin and Houthakker, 1950-51, and Neary and Roberts, 1980), less energy has been devoted to understanding how the rationing of 'bads' might work, in a world where virtually all rations are directed to such products. For examples: most drugs require a prescription from a physician and are sold in limited quantities; bars and betting establishments are limited in their hours of operation; and many toxic products cannot legally be sold to minors.

The theory and simulations we develop suggest that a workplace ban should have an imperceptible impact on low number-of-cigarette smokers, that substitution into adjoining periods should be strong for medium-number smokers, and that a ban should only really bite for heavy smokers. To test this prediction we estimate quantile regressions of the log of number of cigarettes smoked on a range of covariates that includes a variable denoting whether the individual is subject to a workplace ban or not. The data are individual-level from the Canadian Community Health Survey of 2003. The theoretical conjecture is confirmed, and the data further indicate that restrictions on smoking in the home are an order of magnitude stronger than workplace bans, even after instrumenting. Our policy conclusion is that the effectiveness of smoking bans in the workplace depends critically upon whether there exist limits on smoking in the environment to which smokers may substitute.

The paper is developed as follows. Section two describes the public policy and toxicological backgrounds to the issue at hand. Section three develops a quantity-intensity-timing model of smoking during a typical working day. It contains parameterizations and a solution algorithm. Section four assesses the impact of a workplace ban within the context of the theory. Section five describes the data used in the estimation section. Section six contains the main econometric results. Conclusions are offered in the final section along with some caveats on what remains to be learned.

# 2 Background

## 2.1 Public Policy

While tax increases were once almost the sole policy instrument aimed at reducing tobacco use, currently governments and municipalities worldwide are relying progressively on smoking bans in public places, the workplace, and even the, once considerd sacred, five Bs: bars, billiard halls, betting shops, bingo halls and bowling alleys. Some of the earliest municipal ordinances were enacted in California around 1990 (see Moskowitz et al, 2000). In part bans have been introduced out of the recognition that the effectiveness of ever higher taxes is limited, on account of the incentive they provide for illegal production and trans-border shipment[1] , and in part because bans are seen as an additional and distinct measure in the fight against tobacco use. They have become part of what is now termed the public health move to 'denormalize' smoking. As a measure of public policy, smoking bans have two objectives: to induce smokers to smoke fewer cigarettes, or even quit smoking, in the interests of their own health; and to protect other individuals in the environs of smokers from the impact of environmental tobacco smoke (ETS), also known as second hand smoke (SHS). This paper focuses primarily upon the first of these impacts. A growing and inconsistent literature documents the possible impact of bans on hospital admissions due to acute myocardial infarction - Meyers et al, 2009, and Lightwood and Glantz, 2009, take one stance, but this is strongly rejected by Shetty et al, 2009.

While health groups universally support the implementation and extension of strictures on

[1] As of 2006, more than one quarter of cigarettes sold in Canada were supplied illegally (Gfk Research Dynamics, 2006, and ConvenienceCentral, 2006), while a figure of 22% is proposed in West et al (2008) for the UK.

smoking in places shared with others, some research has been less than fully supportive. For example, Adams and Cotti (2008) propose that bans in bars have been found to encourage patrons to seek out bars in adjoining jurisdictions where smoking is not banned, with the consequence that road and vehicle accident rates increase as a result of driving further under the influence of some amount of alcohol.

The strength of bans (and the level of taxes) varies widely, depending upon the degree of anti-tobacco 'sentiment' in the jurisdiction in question (e.g. deCicca *et al* 2006). Sentiment against tobacco control is stronger in states or regions where tobacco is grown. For example, Kentucky, Virginia and the Carolinas have lower tax rates on cigarettes than Massachusetts, because tobacco furnishes a livelihood for many in the former states (*Tobaccofreekids*). While anti-tobacco sentiment may well translate into more widespread bans on public place use, in the present paper we are less concerned with the source or motivation for bans than with their impact.

On the theoretical front, public policy interventions against smoking have received support from several recent developments that have addressed the implications of deviations from the assumptions of the traditional utility-maximizing model: Gruber and Koszegi (2006) and O'Donohue and Rabin (2001) have developed policy measures based on models of time inconsistent behaviour or projection bias, while Bernheim and Rangel (2004, 2005) have developed a framework in which environmental cues are capable of triggering mistakes on the part of the brain's decision mechanism. The former propose internality-correcting taxes, and the latter a correction to environments that may cue decision mistakes resulting in excessive drug consumption. These models stand in contrast to the rational addiction (RA) model of Becker and Murphy (1988) and Becker, Grossman and Murphy (1994), where individuals are capable of consuming a toxic substance 'rationally'. The essential element in the RA models is that the consumer correctley recognizes the impact of current decisions on future states, and smoking may be rational if the future is sufficiently discounted or if current consumption has just a 'small' impact on the utility of future consumption. In this context, public policy measures designed to reduce smoking could be in the interests of individuals exposed to second hand smoke, but not in the interests of rational smokers.

While the model that is developed in the present paper focuses upon intra-day behavior, it is conditioned upon an individual's degree of addiction, and past experience. Furthermore, to the extent that bans or restrictions on smoking can alter the current/flow behavior of an individual, this in turn impacts the stock of accumulated experience with tobacco and hence impacts future smoking choices.

## 2.2 Toxicological Basics

An individual who smokes an average number of cigarettes per day at an average degree of intensity, ingests about one milligram of nicotine per cigarette (e.g. Perez-Stable *et al*, 1998). Very few smokers ingest less than 0.8 milligrams or more than 1.4 milligrams. African Americans tend to smoke more intensively, though whether this is due to a higher genetic disposition or their tendency to smoke mentholated cigarettes, which reduce the burning sensation, is still a somewhat open question (Benowitz *et al*, 2004). In contrast, Chinese Americans smoke many fewer cigarettes than occidentals, primarily because nicotine stays in their system for a longer time period and therefore satisfies the brain's need for the substance for a longer duration (Benowitz et al 2002).

As a starting point, figure 1 below is instructive. It is taken from Jarvis *et al* (2001a), and maps the cotinine level (vertical axis) in the saliva samples of individuals who smoke cigarettes of varying strength (horizontal axis). Cotinine is a metabolite of nicotine and has a half life of about 20 hours, whereas nicotine has a half-life of one hour. Consequently, whatever nicotine content may be present in a blood or saliva sample, it is a poor indicator of the amount of nicotine actually ingested in a 24-hour period. Cotinine content is therefore a standard indicator in studies where such samples are used.

The strength of cigarettes is traditionally determined by smoking machines (Benowitz *et al* 2005, Kozlowski *et al* 1998, US DHHS, 2000): cigarettes are inserted into a machine receptacle; the machines then puff on the cigarettes and a measure is taken of the milligrams of nicotine (and other toxins) inhaled by the machine for many different cigarette brands. Each brand therefore has a nicotine 'standard', and it is this standard that is measured on the horizontal axis.

Apart from the high degree of variability in cotinine levels of individuals who smoke a given strength of cigarette, a stark feature of figure 1 is the very moderate increase in cotinine registered as the strength of cigarette increases. A similar figure is to be found in Adda and Cornaglia (2006), indicating that the amount of cotinine in saliva increases equally moderately in response to increases in the <u>number</u> of cigarettes smoked .

In sum, individuals seem to compensate strongly in their nicotine intake in response to different strength cigarettes and different numbers of cigarettes smoked. The reason that individuals do not smoke each cigarette to its maximum possible nicotine yield is that, while smoking cigarettes more intensively results in additional nicotine and other ingredients that give greater pleasure to the brain's receptors, more intensive smoking also yields more carbon monoxide that can induce dizziness or mild nausea. These two effects form a trade-off for the individual smoker, and together they determine an internal solution for intensity: whereas nicotine provides pleasure for some time after being inhaled, <u>during the time of smoking</u> inhalation also provides disutility on account of the carbon monoxide. Consequently, an optimal degree of intensity (conditional on a given number of cigarettes) is where the marginal disutility from greater intensity during the inhalation phase equals the marginal utility from the additional nicotine for the period during which it remains in the body. The time dimension of this trade-off, and the time-impact of nicotine are critical to understanding the compensatory behaviours that smokers may adopt in response to the imposition of bans that declare certain extended periods of the day to be off-limits to smoking.

# 3 A Quantity-Intensity-Timing Model of Nicotine Intake

## 3.1 A model of individual behavior

To formalize the foregoing, suppose a smoker ingests $N$ units of nicotine[2] at time $t_1$. Then, the amount $Ne^{-\delta(t-t_1)}$ of nicotine resides in the system at any time/instant $t$ thereafter, where $\delta$ is the known decay rate - that is, the decay rate yielding a half life of one hour. A smoker gets positive utility $U_p$ from this nicotine and let us suppose that this is of the form $U_p = N^{\alpha}$ where $\alpha < 1$[3] . It follows that, in the interval $\{t_1, t_2\}$, utility is the integral

$$\int_{t_1}^{t_2} N_{t_1}^{\alpha} e^{-\alpha\delta(t-t_1)} dt \tag{1}$$

If an individual smokes $c$ cigarettes per day, and inhales $N$ units of nicotine from each, starting at instant $t_1$ and ending at $T$, then utility is the sum of utility in each of the $c$ subperiods

$$U_p = \sum_{i=1..T-1} \left( \int_{t_i}^{t_{i+1}} N_{t_i}^{\alpha} e^{-\alpha\delta(t-t_i)} dt \right), \tag{2}$$

where $N_{t_i}$ is the amount of nicotine in the system at the start of each interval. The $c$ intervals are bounded by the $c + 1$ points or instants $t_1..t_T$.

The choice of intensity $N$ is determined both by the amount of pleasure it yields throughout the day through nicotine, and by the short-term disutility it generates on account of the associated nausea that, in turn, is determined by the rate of inhalation. For the moment this disutility is instantaneous; it will have a discrete time dimension in the numerical optimization. Accordingly, defining the disutility $U_d$ associated with this latter impact by $U_d = N^{\phi}$, the net utility $U$ from daily smoking is

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[2] The word 'nicotine' should be interpreted broadly in this context. Cigarettes generate utility as a consequence of inhaling a variety of substances. Toxicologoists believe that nicotine is the most important of these. Thus we do not view nicotine gum or a nicotine 'patch' as being identical to cigarettes.

[3] This condition implies that the marginal utility of nicotine intensity approaches infinity as intensity tends towards zero. Accordingly, this specification guarantees that an individual will always choose some positive amount - higher prices may induce reduced consumption but not quitting. Quitting can be incorporated by assuming that there exists a fixed cost to smoking - perhaps a stigma cost. In a world of indexed tastes, smokers are those individuals whose preferences are such that they obtain a surplus above this value. Since a workplace ban reduces utility, those individuals just on the smoking margin may quit if a ban results in less surplus than the fixed cost.

$$U = U_p - U_d = \sum_{i=1..T-1} \left( \int_{t_i}^{t_{i+1}} N_{t_i}^{\alpha} e^{-\alpha\delta(t-t_i)} dt \right) - cN^{\phi}, \tag{3}$$

In intuitive terms, the above states that if, for example, a smoker were to smoke one cigarette each hour, the resulting stock of nicotine in the body yields utility throughout the day, but that there is some disutility in the initial phase of each hour on account of the nauseous impact of the carbon monoxide associated with inhalation. It is this negative utility potential of high-intensity smoking that limits the intake of nicotine to a level below its potential maximum per cigarette.

## 3.2 Optimization and solution algorithm

For a given set of relative prices between cigarettes and other goods, the consumer must choose the optimal number of cigarettes, the optimal spacing during the day of such cigarettes, and the optimal intensity with which to smoke them. The solution strategy is sequential: we optimize on the timing of each cigarette, conditional upon a given number of cigarettes purchased; then the optimal intensity can be chosen; finally, relative prices determine the quantity of cigarettes purchased. The timing of the smoking decision is obviously critical in a model incorporating bans on smoking during particular phases of the day. Bans will impact the quantity purchased, distort the timing and increase the intensity.

Formally, in terms of equation (2) above, the smoker first chooses the set $\{t_1, t_2..t_{T-1}\}$, conditional upon the number of cigarettes smoked. Denoting the vector of time choices by $\bar{t}_i$, the choice of timing can be separated from the choice of intensity, since the maximand can be written as:

$$Max_{\{\bar{t}_i, N;\ c\}} \quad U = N^{\alpha} \sum_{i=1..T-1} \left( \int_{t_i}^{t_{i+1}} e^{-\alpha\delta(t-t_i)} dt \right) - cN^{\phi} = N^{\alpha}V - cN^{\phi}, \tag{4}$$

where $V$ is the positive utility that accrues during the day to smoking each cigarette at unit intensity $N = 1$. Thus, total positive utility can be written as the product of the level of nicotine intake raised to the power of $\alpha$, and $V$. It is clear immediately that the program defined by equation (4) is separable in the choice of timing and intensity.

This program can be integrated with respect to $t$, and then a set of choices for the $c$ time period boundaries $t_i$ may be obtained from the gradient vector $\partial U_p/\partial t_i = 0, \forall i$. Integrating yields

$$U = N^{\alpha} \sum_{i=1..T-1} \frac{e^{-\alpha\delta(t_{i+1}-t_i)} - 1}{-\alpha\delta} - cN^{\phi}. \tag{5}$$

Differentiating this with respect to each $t_i$ yields conditions that are difficult to work with. To see this, suppose an individual smokes 30 cigarettes per day. The choice of when to smoke the second or third cigarette will have consequences on the utility obtained from every subsequent cigarette - because nicotine decay is incomplete from interval to interval. Postponing the time of the next cigarette means that more nicotine is carried to all subsequent time intervals. Consequently, the choice of, say, $t_2$ influences the utility obtained in all 30 time intervals. Accordingly, to reduce the dimensionality of the problem to manageable proportions, we adopt a search algorithm that is based on an approximate set of first order conditions in making the timing choices.

Since the decay rate for nicotine is moderate, in practice a very good numerical approximation to the underlying first order conditions can be obtained by limiting attention to the impact of the choice of any $t_i$ on a small number of intervals. In particular, focussing on the utility obtained in the intervals on either side of any $t_i$, and two further future periods, means that an approximate first order condition can be obtained by differentiating

$$Z = N_{t_{i-1}}^{\alpha} \frac{e^{-\alpha\delta(t_i-t_{i-1})} - 1}{-\alpha\delta} + N_{t_i}^{\alpha} \frac{e^{-\alpha\delta(t_{i+1}-t_i)} - 1}{-\alpha\delta} + N_{t_{i+1}}^{\alpha} \frac{e^{-\alpha\delta(t_{i+2}-t_{i+1})} - 1}{-\alpha\delta} + N_{t_{i+2}}^{\alpha} \frac{e^{-\alpha\delta(t_{i+3}-t_{i+2})} - 1}{-\alpha\delta} \tag{6}$$

with respect to $t_i$, using the relations

$$N_{t_i} = N_{t_{i-1}} e^{-\delta(t_i-t_{i-1})} + N; \quad \frac{\partial N_{t_i}}{\partial t_i} = N_{t_{i-1}}(-\delta)e^{-\delta(t_i-t_{i-1})}; \quad \frac{\partial N_{t_{i+1}}}{\partial N_{t_i}} = e^{-\delta(t_{i+1}-t_i)}. \tag{7}$$

This yields, after some rearranging of terms:

$$
\begin{aligned}
\frac{\partial Z}{\partial t_i} &= N_{t_{i-1}}^{\alpha} e^{-\alpha\delta(t_i - t_{i-1})} \\
&\quad - N_{t_i}^{\alpha} e^{-\alpha\delta(t_{i+1}-t_i)} + \left(e^{-\alpha\delta(t_{i+1}-t_i)} - 1\right) N_{t_i}^{\alpha} N_{t_{i-1}} e^{-\delta(t_i - t_{i-1})} \\
&\quad - \left(e^{-\alpha\delta(t_{i+2}-t_{i+1})} - 1\right) N_{t_{i+1}}^{\alpha-1} N e^{-\delta(t_{i+1}-t_i)} - \left(e^{-\alpha\delta(t_{i+3}-t_{i+2})} - 1\right) N_{t_{i+2}}^{\alpha-1} N e^{-\delta(t_{i+2}-t_i)} \quad (8)
\end{aligned}
$$

The solution algorithm starts by allocating the cigarettes evenly over the whole smoking day, thus determining a starting set of $t_i$ values. We then compute $\partial Z/\partial t_i$ at each such value of $t_i$, and adjust the $t_i$ that corresponds to the largest gradient. If that gradient is negative its $t_i$ value is reduced, if positive, the value is increased. Each time a value of $t_i$ is adjusted the new value of $U_p$ is calculated, a new gradient vector is calculated and some $t_i$ is again adjusted. The routine stops when $dU_p < 0.001$. Since the numerical value of utility typically falls in the range $\{50, 150\}$, this criterion means that the value of the objective function is changing by less than one in one hundred thousand at the final iteration[4] .

The smoking day is specified to lie between 7:30 am and 10:00 pm. This is broken into 145 units of 6 minutes each, on the grounds that it takes about 6 minutes to smoke a cigarette (a frequent pattern is one where the smoker inhales perhaps ten times, with 35 second breaks between puffs - see Hammond *et al, 2006*). So the solution algorithm yields integer values for the $t_i$ vector in the range $\{1..145\}$.

### 3.3 Optimizing on intensity

An optimal value of intensity $N^*$ is obtained from equation (4) above:

[4] While a sufficient condition for this mechanism to attain a maximum is that the Hessian be negative semi definite, we cannot demonstrate that it has this property because of the complexity of the associated Hessian. The function will attain a maximum if it has a unique optimum and positive first derivatives everywhere in the $t_i$ space. While the order of the problem makes it difficult to establish this in the in the general case, we have explored exact solutions to the maximand where there are a small number of intervals. In such cases the numerical solutions obtained from the solution algorithm match the analytical solutions, and the 3D images of the function indicate that it has a unique maximum.

$$
\begin{aligned}
\partial U/\partial N &= \alpha N^{\alpha-1}V - c\phi N^{\phi-1} = 0 \\
N^* &= V^{1/(\phi-\alpha)} \left(\frac{\alpha}{c\phi}\right)^{1/(\phi-\alpha)}.
\end{aligned} \tag{9}
$$

For intensity to be decreasing in the number of cigarettes (and thus match the evidence), the parameters in the model must satisfy the relation implied by the condition $\frac{\partial N^*}{\partial c} < 0$. Experimentation suggests that a range of values satisfy this requirement. But the parameter values must also be able to generate intensity outcomes that fall in the range of 0.8 mg to 1.4 mg of nicotine per cigarette, in order to conform to observed magnitudes. We find that pairs in the neighbourhood of $\{\alpha = 0.3, \quad \phi = 2.5\}$ satisfy both of these requirements. The intuition on the relative magnitudes of $\alpha$ and $\phi$ is straightforward: the smokng of the cigarette lasts for a much shorter period than the utility-yielding nicotine stays in the body. And to obtain the required intensity tradeoff, the immediate disutility from the high intensity must exceed the immediate positive utility from the nicotine, since the latter is longer lasting.

### 3.4 Prices quantities and demand functions

To this point, the optimal timing and intensity rules are conditioned upon a given quantity consumed. The link between a chosen quantity and a given price can be established easily by invoking a quasi-linear utility structure:

$$
W = U(c) + \theta y, \tag{10}
$$

where $y$ represents other goods. Normalizing the price of $y$ at one and defining $p$ as the price of cigarettes the optimality condition is

$$
\frac{U_c'}{p} = \theta. \tag{11}
$$

In this quasi-linear framework a change in price requires a new quantity of cigarettes such that marginal utility divided by price is restored to the initial value $\theta$. Numerically, the value of utility is obtainable for any quantity of cigarettes purchased (maximizing simultaneously on timing and intensity), and a marginal utility schedule drops out of this.[5]

# 4 Assessing the Impact of Smoking Bans

## 4.1 Modelling workplace Bans

Smoking bans come in different forms. The most common one, and one which would be anticipated to have the greatest impact on behaviour, is a ban on smoking in the workplace. Workplace bans effectively make smoking more difficult and costly for about one half of the effective day, and therefore may be expected to have a substantial impact on behaviour.

Within the context of a utility maximizing agent, subject to a budget constraint, such bans are best envisaged as increasing the cost of a cigarette smoked during these periods: if individuals choose to smoke a cigarette during their working day, it must be outside the confines of their office or workshop. This involves a time cost that changes radically the price of a cigarette. During unrestricted segments of the day a single cigarette may cost in the range of 20 - 40 cents, depending upon whether it is purchased in Europe or the US; but during the restricted segments of the day an individual must incur the time costs of smoking. Approximately one sixth of an hour is required to smoke one cigarette (ten minutes – six to smoke and four to commute out doors), and so the effective cost to a smoker with a \$21 per hour job of one such cigarette approaches \$4.00 – a tenfold increase in price during the working day in this instance.

Conceptually the solution to the problem of choosing the optimal number of cigarettes to purchase, when to smoke them and how intensively to smoke them is not difficult: the optimality condition is that the marginal utility per dollar must be the same for a cigarette smoked during the working day as one smoked during the unrestricted segments of the day. And each of these must

[5] For numerical purposes, in order to get a continuous and differentiable marginal utility schedule, we regress the utility values obtained in the optimization on a low-order polynomial in c.

equal the marginal utility of consumption on other goods, which, by assumption of quasi-linear utility, is constant and ascertainable from a base parameterization of the model.

To understand the impact of a workplace ban, consider figure 2 below. The day runs from 7:30 am to 10:00 pm at night, and the working day from 9:00 am to 12:30 and from 13:30 to 17:30. If the price during the working/restricted day, $p_r$, is ten times the price during the unrestricted period, $p_u$, then the marginal utilities must bear the same tenfold relationship in equilibrium:

$$\frac{MU_u}{p_u} = \frac{MU_r}{p_r} = \theta. \tag{12}$$

A requirement that marginal utility during the working day increase by a factor of ten will require a substantial reduction in quantity consumed during that period. As a consequence of such a quantity reduction, the marginal utility of cigarettes smoked during the unrestricted periods must rise. The mechanism by which a new equilibrium is attained depends upon the fact that cigarettes smoked in any phase of the day contribute to the stock of nicotine in the body beyond the smoking period.

In the first place, cigarettes smoked in the initial unrestricted period of the day (morning) have a carry-over utility value: each morning cigarette produces a stock of nicotine that has lasting utility value through the morning work period. These early morning cigarettes produce a greater marginal utility in the absence of smoking during the morning work period: the nicotine stock they produce is not augmented further by work-time cigarettes, and therefore their marginal utility increases. We term this the *knock-on* effect.

Consider now the unrestricted evening period. A reduction in afternoon smoking means that the stock of nicotine in the body is depleted when the evening period arrives. In turn this implies that the marginal utility of cigarettes smoked in the early phase of the evening period is high and therefore it becomes optimal to smoke more cigarettes during this early evening phase than in the absence of an afternoon smoking ban. This impact we term the *nicotine deficit* impact.

It is clear that the mid-day response to a ban on morning and afternoon work time smoking will likewise demand an increase in the number of cigarettes smoked, because *both* the nicotine deficit effect and the knock-on effect are in play.

This then is the intuition underlying the results for the computable model. While the following section of the paper estimates some quantile regressions, it is instructive to examine how much smoking substitution is implied by the calibrated model. To get a sense of this we model the optimal response behaviour of a heavier than average smoker - one who smokes 18 cigarettes per day in a 'no restricions' workplace. The price of a cigarette is assumed to be 40 cents (corresponding to about 5.50 *Euro* per pack or eight Canadian dollars – somewhat higher than the current US price).

Optimality requires a smoking strategy that satisfies eq. (12) above and in addition that allocates a given daily total of cigarettes across all five periods such that utility is maximized. That is, defining the intervals $I$ as $I1..I5$, and the number of cigarettes smoked in each interval by $i, j, k, l, m$, a utility maximum for any total $c$ requires that

$$U(I1_i,\ I2_j,\ I3_k,\ I4_l,\ I5_m) > U(I1_{i'},\ I2_{j'},\ I3_{k'},\ I4_{l'},\ I5_{m'}) \qquad \forall \quad i',\ j',\ k',\ l',\ m'. \tag{13}$$

where

$$i + j + k + l + m = c = i\prime + j\prime + k\prime + l\prime + m\prime. \tag{14}$$

The dimensions of the optimization are reduced by noting first that the initial cigarette of the day should be smoked at the first possible moment. This is because postponing that cigarette would essentially waste a small amount of nicotine at the end of the day. Second, it is straightforward to show that, with a sufficient difference between the full price of a cigarette in the unrestricted and restricted intervals, the last cigarette to be smoked in intervals $I1$ and $I3$ should be at the latest possible moment in those intervals (a cigarette in the following instant costs ten times as much but is a close substitute). By the same reasoning, the first cigarette smoked in intervals $I3$ and $I5$ should be at the first possible instant in those intervals on account of the nicotine-deficit effect.

### 4.2 Numerical results and behaviours

The results for this particular experiment are contained in table 1. At a price of \$0.4 per cigarette in the unrestricted interval, and \$4.0 in the restricted intervals, it is optimal to reduce total purchases from 18 to 16, to smoke none in the restricted intervals and to distribute the cigarettes in a $\{I1 = 6,\ I2 = 0,\ I3 = 5,\ I4 = 0,\ I5 = 5\}$ pattern, as indicated in column (ii).

There are several notable aspects of this experiment. First is the allocation within the day: lunch time smoking increases due to a combination of the nicotine-deficit effect and the knock-on effect, each described above, operating in the mid-day interval. An optimal plan involves a quick nicotine catch-up when the lunch interval arrives, and simultaneously a stocking up for the afternoon period. In contrast, the evening allocation should not be so great as to loose the utility value of nicotine in the body when the end of the day arrives – it is optimal to have a low stock of nicotine at the end of the day, and therefore to avoid consuming too large a number in the evening interval.

The second notable aspect of the constrained decision making is that condition (13) is satisfied at a value of $c$ that is surprisingly close to its unconstrained value (16 rather than 18). This result is due to the stock-flow nature of the model. A reduction in smoking during the restricted intervals increases the marginal utility of cigarettes in the unrestricted periods.

Third, the optimal value of intensity increases - see the final row in table 1. This occurs on account of the increase in the marginal utility that the reduced number of cigarettes entails, in turn requiring an increase in the disutility of intensity - which occurs at a higher level of intensity. Consequently the reduction in nicotine ingested is even less than the amount suggested by the reduction in quantity consumed.

Fourth, the switch from smoking during the working day to the unrestricted intervals sees a jump in morning smoking, despite the reduction in the total number of cigarettes smoked. Evening smoking is affected little, even though it has a substantially greater duration, for the reason that the utility value of cigarettes smoked at the end of the day is not as great as at the start of the day. The model suggests that virtually all of the impact of the workday smoking ban is transferred to the morning and mid-day periods, and very little to the evening period. This predicted increase in morning smoking could increase exposure to SHS on the part of other family members. Jarvis *et al* (2000, 2001b) report that cotinine concentrations among children in the UK have fallen over time as a result of lower exposure levels globally; they also report that cotinine levels among non smoking partners increase with the number of cigarettes smoked by a smoking partner. And while the cotinine concentrations among non-smokers are typically no more than one percent of a smoker, Hackshaw *et al* (1997) report that the difference in cotinine levels between partners of non smokers and smokers is sufficiently large to be significant in the sense of inducing higher morbidity risk.

Fifth, this model suggests that high-income individuals should respond more to a workplace ban than lower-income individuals because their opportunity cost if time is greater. Gruber and Koszegi (2004) propose that high-income groups have *less* elastic responses than low-income groups to changes in the purchase prices of cigarettes. If they are correct, then the impact of different reduction measures (taxes versus bans) varies by income groups. Our econometric results below provide strong support for this observation.

For illustrative purposes, the optimal nicotine patterns for a restricted and unrestricted day are represented in figure 3, and the corresponding utility flows in figure 4.

Sixth, demographic and peer impacts should be important: if A becomes subject to a workplace smoking ban and wishes to substitute his smoking towards the home in the morning, the ban may be more effective if he has a non-smoking partner. However, if he has a smoking partner B, she too may wish to smoke more in the morning at home, and A and B may together facilitate this substitution. We investigate this empirically below by using information on the home demographic environment of the smoker.

Finally, we observe in practice that individuals do smoke during the working day - frequently congregating at the workplace entrance at mid morning or mid afternoon. Such observations are consistent with the model we have developed and with the simulations reported above. It may be optimal for low wage smokers to incur the higher price during work hours; or it may be the case simply that the employer is bearing the cost of the workbreak. It follows that the number of cigarettes smoked in this regime must be at least as great as in the regime where no smoking is permitted during work.

# 5 Empirical Evidence

## 5.1 Econometric Framework

In this section, we use micro data to test the predictions of the theoretical model. In particular, we examine (i) the simultaneous impact of workplace and home bans in the same regression, with a view to shedding light on their relative impacts in reducing smoking; (ii) if a workplace ban has stronger impacts on heavy smokers than on light and medium smokers; and (iii) whether high-income individuals respond more to a workplace ban than lower-income individuals on account of their opportunity cost of time.

The smoking outcome that we focus on is the log of the number of cigarettes smoked per day per smoker (CigQ). Our regressions are of the form:

$$log(CigQ) = \alpha Workban + \beta Homeban + X\Phi + Provincefixedeffects + error \tag{15}$$

Workban is a dummy for workplace smoking ban (1 if there is a ban, including complete and partial bans, and 0 if there is none); Homeban is a dummy for restrictions on smoking at home (1 if there is some restriction, 0 otherwise); X is vector of socio-economic variables including gender, age, education level, income, marital status, household size and language of the respondents. We include province fixed effects to capture province-specific differences including cigarette taxes and prices. Therefore, identification of workplace ban and home ban effects is achieved by within-province variation in these two variables. All our regressions use sample weights and adjust standard errors for clustering at the province level.

Equation (15) is estimated using three methods. We begin with OLS estimation which provides us with preliminary estimates. Then we apply quantile methods, to better understand how different segments of the distribution of smokers respond to bans. Next, given a home ban is likely to be endogenous,[6] we instrument it using dummies indicating whether there are children under 5 years of age in the household, and whether the individual belongs to a volunatary organization.

## 5.2 Data

The data used in our analysis are from the 2003 Canadian Community Health Survey (CCHS).[7] The cross sectional CCHS surveys are conducted biennially, covering several health aspects of the population. In particular, there is rich coverage of smoker behaviors, including the number of cigarettes smoked per day as well as restrictions on smoking at the workplace and in the home.[8] It also has detailed information on income, education, and other demographic variables.

Table 2 presents summary statistics for the data. Because we study the effects of smoking bans on smoking quantity, our sample consists of daily smokers and thus excludes those categorized as occasional smokers. The average number of cigarettes smoked per day is 16.1.[9] 57% of workplaces impose smoking bans; the home ban rate is lower, at 37%. Almost half of our sample is male, and 13.7% of respondents' families have one or more children aged five years or younger.

[6] Evans et al (1999) propose that a workplace ban may be endogenous due to workers' self selecting into workplaces on the basis of whether or not there may exist a smoking restriction. We think this is possible but is unlikely to be of large magnitude in the modern era given how extensive are such bans. Furthermore, our data do not yield a good instrument for the workplace ban. Most importantly, our focus on the endogeneity of home restrictions is driven by our finding that the effects of the latter are much stronger than those of workplace bans.

[7] CCHS 2003 cycle is chosen for two reasons. First, the question on home smoking restrictions is posed only to non-smokers in previous CCHSs. Second, questions on home and workplace ban are asked only in a sub-sample of the 2005 CCHS survey, which therefore suffers from sample size problems.

[8] The question asked on workplace ban is: "At your place of work, what are the restrictions on smoking?" Possible responses include: (i) Restricted completely, (ii) Allowed in designated areas, (iii) Restricted only in certain places, (iv) Not restricted at all. For the home ban, the question is: "Are there any restrictions against smoking cigarettes in your home?" and the answers are binary: (i) yes, (ii) no.

[9] CCHS surveys accept 99 cigarettes per day as maximum. This number is too large to be credible and population representative. We therefore exclude those who report smoking more than 60 cigarettes a day from our sample.

The average age of the smokers in our sample is 42.[10] and 46% of the sample reports living with a partner. Income is categorized into 5 levels, with 34% of respondents earning less than $15,000 a year and approximately 15% obtaining more than $50,000. Nearly half of the sample has some post-secondary schooling. Lastly, two thirds of the respondents use English as their main language.

## 5.3 Regression Results

### 5.3.1 OLS Estimation

The results from OLS estimation are presented in Table 3. Column 1 results contain a workplace ban dummy but not a home ban control. The workplace ban coefficient is negative and statistically significant, indicating that it reduces smoking by about 9% on average - less than two cigarettes perday[11] . In column 2, we keep the socio-economic controls but replace the workplace control by a home ban dummy. The resulting home ban coefficient is also negative and statistically significant. Its effect is almost three times larger than that of a workplace ban, suggesting that it might reduce the numebr of cigarettes smoked on average by four per day.

Because the effect of a workplace ban might be included in the home ban estimated effect, in column 3 we include both home ban and work ban dummies in the following column of results. The effect of the workplace ban decreases slightly but is still statistically significant. The home ban coefficient also drops slightly, but remains three times are large as the workplace ban coefficient. This suggests that home bans play a considerably more important role than workplace bans in reducing smoking. Combined, the overall effect is to reduce daily consumption by 30% - about five cigarettes. This is a large number and we examine the potential endogeneity of the home ban below by instrumenting it.

The remaining variables have the expected effects. Male smokers light up more frequently than

[10] Age is coded into 15 categories in the dataset.

[11] The dummy variable coefficients are interpretable as percentage differences in the number of cigarettes smoked relative to the 'omitted category' individual in the regression. This individual smokes just very slightly less than the median individual, so we can reasonably interpret the coefficients on the ban variables as percentage impacts relative to a typical median individual.

their female counterparts. Age and income effects both follow a mildly inverted U pattern. Smokers in middle income groups smoke most heavily. Note that this does not imply that individuals with higher income smoke more, given that the participation rate is much lower among those with higher incomes. Higher education is monotonically correlated with lower number of cigarettes smoked per day. Meanwhile, those who speak English smoke more heavily than those speaking other languages. The dummy Student, included to control for those currently at school, has a large negative coefficient, indicating that students smoke less than those who are not. Its large magnitude compared with the coefficient on college degree group probably indicates a cohort effect. That is, those who already have a college degree used to smoke a lot more as students than those who are currently students.

#### 5.3.2 Effects by Income Groups

We now test whether the impact of a workplace ban varies with income. If our behavioral model of smoking is correct, it implies that the real cost of smoking a cigarette is larger for those with higher incomes: the largest part of the total cost of a cigarette in a regime with a workplace ban is the time cost. Hence higher income individuals have a greater incentive to reduce their smoking than those on lower incomes. The results are presented in Table 4. While a work ban has no perceptible impact on the lowest income groups, it becomes more effective for higher income groups, and has the largest effect at the top of the income distribution. There thus appears to be a threshold, somewhere below the middle of the income distribution, where a workplace ban becomes more effective on account of time costs. This evidence supports the theoretical model developed in the earlier part of this paper. [12] The home ban effects are again large, though somewhat more uniform across income groups than the workplace bans. We also estimate the model for different educational groups. The results are presented in Table 5. Given the high positive correlation between income and education, it is not surprising that we find effects similar

[12] Besides the interpretation of higher opportunity costs of time for higher income groups, peer effects may generate this outcome: if higher income smokers hold more important positions in an organization they may be more subject to social pressure to avoid taking smoking breaks at the entrance to their workplace.

to those when the sample is disaggregated by income group. Specifically, a workplace ban has no impact on the lowest educational group but becomes more effective for higher educational groups.

#### 5.3.3 Heavy Smokers and Lighter Smokers: Quantile Regressions

We now test the second prediction of our theoretical model - that workplace bans have larger impacts on heavy smokers, by estimating a quantile regression which includes both workplace and home ban controls. The results for selected quantiles are presented in Table 6. The effects of a workplace ban are quite small throughout, though broadly increasing in going from the low to the high quantiles. The 2.8% reduction at the twentieth quantile amounts to essentially no real impact, despite a significant coefficient. Given that the number of cigarettes smoked per day in this range is in the region of six to seven, the coefficient amounts to stating that the average impact is to take a couple of puffs less per day. At the mid and upper mid ranges the impact becomes more meaningful and averages about 6% - implying a numerical reduction of a little more than one cigarette. In contrast, at the ninety fifth percentile a 9% impact implies a reduction in excess of three cigarettes perday. In sum, the overall effects are again surprisingly small, with meaningful reductions achieved only at the very upper end of the distribution. Furthermore, the results are remarkably consistent with the output of the theoretical model in the preceding section. A smoker smoking 18 cigarettes per day - the value used in our illustrative simulation - lies between the sixtieth and seventieth percentiles, and the simulation indicated that such a smoker would reduce intake by two per day. We were initially surprised that the reduction was so modest, yet there appears strong support for it in the data.

In contrast to a workplace ban, a home ban is considerably more important throughout the whole range of the distribution. The effects in the bottom 60% of the distribution are such as to reduce smoking by one quarter. The percentage reductions decline as we move to the higher percentiles, but the absolute impact increases: a 25% reduction at the lower level may result in a reduction of just two cigarettes, whereas a 12% reduction at the top end reduces the number by as much as five cigarettes per day. Figure 5 describes the impact of each ban at every percentile in the distribution.

To this point it appears that if a smoker is subject to both a work place and a home ban, he will reduce his intake substantially. However, workplace bans, despite the commonly held view, are of less value, and have very little impact outside the top of the distribution. To see if this finding is robust to endogeneity concerns we now present the results for an IV estimation.

#### 5.3.4 IV estimation

The presence or absence of home restrictions could arise from several unobservable sources: first, it may result from negotiations between family members (where the smoker is not classified as an 'individual'), including the smoker. Unfortunately our data base has no information on the smoking behaviour of a partner or spouse. A second channel may arise through home restrictions being a type of committment device used by an individual as a result of poor health or advice from a physician.

Our main instrument for dealing with the endogeneity of the home ban is a dummy indicating whether households have one or more children less than twelve years old. We believe this is a strong instrument: worrying about the effect of exposure to smoke by offspring, parents are more likely to put in place restrictions against smoking at home. This instrument is also likely to be valid, because we expect the only way young children affect their parents' smoking is through pressuring them not to smoke at home, which is captured by the home ban.

Another instrument we use is whether a respondent is a member in a voluntary organization. Being a member of voluntary organization, one would be more likely to adopt a home smoking ban if there are smoking restrictions in the voluntary organizations themselves, and if other members already have smoking restrictions at their homes. Additionally, such membership may denote that an individual is more concerned about the externalities that attend his (smoking) behavior.

The results of the IV regression are shown in Table 7. The first two columns of the table use one of the two instruments, the third column results are based on both instruments being included. The coefficients on home ban from these two just-identified 2SLS regressions are negative, statistically significant and a bit larger than the OLS estimates. This is not at all surprising, because in the context of heterogenous treatment effects, the IV estimate here is LATE (local average treatment effect), and estimates the impact of a home ban on the complier group (i.e. those who impose home ban if having children under 12 years old and those who do not if having no children under 12). This complier group is most likely to respond to the home ban. In contrast, OLS estimates the mean effect on the whole population.

The F statistics for excluded instrument from first stage regressions are 227 and 29 which exceed the conventional critical value of 10 used to assess weakness of instruments. Thus, they are not weak instruments.

We next include both instruments in our regressions. The home ban coefficients do not deviate much from the just-identified cases. More importantly, there is little difference between the results estimated by 2SLS and LIML. This is reassuring because it is well known that 2SLS is likely to be biased, especially in the presence of weak instruments, and that LIML provides better estimates than 2SLS in finite samples. Also, the tests indicate that the nulls of weak instruments are easily rejected and the nulls of valid instruments cannot be rejected.

# 6 Conclusion

It is important to recognize that this paper is about behavior and incentives. It is not about social well being, nor is it about the appropriate role for governments in controlling tobacco use. This given, the results are are remarkably clearcut. If we take seriously the idea that smokers should substitute from periods when smoking is prohibited to periods when it is not, then the imposition of bans on smoking in the workplace should be small for most smokers. Our theoretical model has additional predictions: (i) heavy smokers should be the ones most heavily impacted by a workplace ban, (iii) higher income smokers experience a higher time cost when a workplace ban is imposed and therefore should exhibit greater reductions, and (iii) smokers have an incentive to smoke their reduced number of cigarettes more intensively.

Our empirical work indicates that the groups most affected by bans (in an absolute sense) are those at the top of the smoker distribution and at the top of the income distribution, the former because substitution becomes more challenging, and the latter on account of their elevated time costs.

A new finding in this research is that the impact of restrictions on smoking in the home is an order of magnitude larger than the impact of workplace bans. The growing spread of restrictions on smoking in the home means that workplace bans are more effective now than in an era when such home restrictions were rare: ultimately the effectiveness of government-imposed work bans depends upon the inability of smokers to switch their smoking to the home or extra-workplace environment. Consequently, the direct impact of government decrees on workplace bans as stand-alone policies would appear to be modest.

These results are consistent with, yet distinct from, those of Evans, Farrelly and Montgomery (1998). They found that the impact of a workplace ban was to reduce smoking by 10% among smokers, whereas we find a reduction in the neighbourhood of 6% for a median smoker. Our data are for a much more recent period (2003) than the data used by Evans et al (1992 and 1993). The number of cigarettes smoked per day has declined dramatically among continuing smokers in that time interval, on account of higher real prices in both jurisdictions (the US and Canada) and evolving social norms. The larger declines they obtain may be a function of the greater difficulty in avoiding bans, given the greater number of cigarettes smoked per day in 1992 and 1993 by a typical smoker.

Finally, how can the health consequences of all of this be assessed? The answer hinges critically upon whether health costs are convex or concave in toxin intake. The severity of the health impact of smoking increases with the amount of smoking: smoking for a greater number of years or smoking more cigarettes per day increases the lifetime probability of tobacco-related morbidity.

For example, Godfredsen *et al* (2005) find that quitters reduce their probability of disease realtive to continuing smokers, and also that moderate smokers have lower risks than heavy smokers. Specifically, they find a near exact proportionate relationship in the relative disease probability between smokers who smoke fewer cigarettes and smokers who smoke more. However, if low-quantity smokers smoke more intensively than higher-quantity smokers, their finding implies that health consequences are convex in the amount of nicotine-correlated toxins in the body. Our quantile regression results indicate that the biggest impact of workplace bans is at the upper tail of the distribution of smokers. As a consequence, a reduction in toxin intake of a given amount in this range of the distribution may lead to a greater improvement in health than an equal reduction at reduced smoking rates. Thus, even if workplace bans do not reduce toxin intake substantially when smokers consume a realtively small number of cigarettes per day, health improvements may still materialize as a result of heavy smokers smoking less, given the observed convexities.

As a last word of caution, it must be recognized that more work needs to done in assessing econometrically the intensity response of smokers to these two types of bans. It it critically important to understand if the impact of home and workplace restrictions may may moderated by such responses.

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Table 1 Optimal smoking patterns with and without smoking bans (7:30am - 10:00 pm)

| | (i) C = 18, Unrestricted | (ii) C = 16, Restricted | (iii)C = 16, Unrestricted |
|---|---|---|---|
| Interval 1 (morning pre work) | 1 | 1 | 1 |
| t = 1 .. 15 | 2 | 2 | 2 |
| | 9 | 4 | 11 |
| | | 12 | |
| | | 14 | |
| | | 15 | |
| Interval 2 (morning work) | 18 | | 21 |
| t = 16 .. 50 | 26 | | 30 |
| | 35 | | 40 |
| | 43 | | 49 |
| Interval 3 (lunch) | 51 | 51 | 58 |
| t = 51 .. 60 | 60 | 52 | |
| | | 56 | |
| | | 59 | |
| | | 60 | |

There are 145 six-minute intervals in this smoking day.

Table 1 Optimal smoking patterns with and without smoking bans (7:30am - 10:00 pm) (continued)

| | (i) C = 18, Unrestricted | (ii) C = 16, Restricted | (iii)C = 16, Unrestricted |
|---|---|---|---|
| Interval 4 (afternoon work) | 68 | | 68 |
| t = 61 .. 100 | 77 | | 77 |
| | 85 | | 87 |
| | 94 | | 96 |
| Interval 5 (evening) | 102 | 101 | 106 |
| t = 101 .. 145 | 110 | 102 | 114 |
| | 118 | 108 | 125 |
| | 127 | 116 | 131 |
| | 133 | 124 | |
| Optimal intensity | 1.054 | 1.081 | 1.094 |

There are 145 six-minute intervals in this smoking day.

Table 2. Summary statistics, CCHS 2004

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Numcigs | 25109 | 16.109 | 8.68165 | 1 | 60 |
| ln(Numcigs) | 25109 | 2.61245 | 0.62735 | 0 | 4.09435 |
| Work Ban | 22567 | 0.57269 | 0.4947 | 0 | 1 |
| Home Ban | 25023 | 0.37074 | 0.48301 | 0 | 1 |
| Child under 5 | 25109 | 0.13601 | 0.3428 | 0 | 1 |
| Male | 25109 | 0.49512 | 0.49999 | 0 | 1 |
| Age | 25109 | 7.2337 | 3.27906 | 1 | 15 |
| Spouse | 25031 | 0.46574 | 0.49884 | 0 | 1 |
| Hhsize | 25109 | 2.3666 | 1.22195 | 1 | 5 |
| English | 25109 | 0.65761 | 0.47452 | 0 | 1 |
| Less than $15,000 | 21716 | 0.34458 | 0.47524 | 0 | 1 |
| $15,000 - $30,000 | 21716 | 0.27068 | 0.44432 | 0 | 1 |
| $30,000 - $50,000 | 21716 | 0.22638 | 0.4185 | 0 | 1 |
| $50,000 - $80,000 | 21716 | 0.12277 | 0.32818 | 0 | 1 |
| More than $80,000 | 21716 | 0.0356 | 0.18528 | 0 | 1 |
| Less than secondary | 24592 | 0.3306 | 0.47044 | 0 | 1 |
| Secondary school | 24592 | 0.21259 | 0.40915 | 0 | 1 |
| Some post-secondary | 24592 | 0.07974 | 0.2709 | 0 | 1 |
| Post-secondary | 24592 | 0.37707 | 0.48466 | 0 | 1 |

Table 3 Workplace ban and home ban effect, OLS estimation

| Variables | Workban only | Homeban only | Workban & Homeban |
|---|---|---|---|
| Workban | -0.0946*** | | -0.0823*** |
| | -0.0163 | | -0.014 |
| Homeban | | -0.242*** | -0.231*** |
| | | -0.0144 | -0.0146 |
| Male | 0.122*** | 0.136*** | 0.127*** |
| | -0.0119 | -0.0104 | -0.0106 |
| Student | -0.234*** | -0.207*** | -0.218*** |
| | -0.0424 | -0.0393 | -0.0439 |
| Age 20-24 | 0.0884*** | 0.0855*** | 0.0821** |
| | -0.0245 | -0.025 | -0.026 |
| Age 25-44 | 0.241*** | 0.224*** | 0.220*** |
| | -0.0334 | -0.0372 | -0.0371 |
| Age 45-64 | 0.326*** | 0.299*** | 0.294*** |
| | -0.0483 | -0.0513 | -0.0509 |
| Age 65+ | 0.175*** | 0.0997** | 0.145*** |
| | -0.0314 | -0.0344 | -0.038 |
| Spouse | -0.00149 | 0.0254* | 0.0181 |
| | -0.013 | -0.0122 | -0.0126 |
| Hhsize | -0.0250* | -0.00838 | -0.00452 |
| | -0.012 | -0.0115 | -0.0109 |

Notes: Robust standard errors clustered at province level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3 Workplace ban and home ban effect, OLS estimation (continued)

| Variables | Workban only | Homeban only | Workban & Homeban |
|---|---|---|---|
| Income_2 | 0.0260** | 0.00327 | 0.0224** |
| | -0.00827 | -0.00856 | -0.00903 |
| Income_3 | 0.0641* | 0.0339 | 0.0658** |
| | -0.0294 | -0.0235 | -0.0286 |
| Income_4 | 0.0799*** | 0.0589** | 0.0902*** |
| | -0.0157 | -0.0206 | -0.0176 |
| Income_5 | 0.143*** | 0.111** | 0.149*** |
| | -0.0373 | -0.047 | -0.0443 |
| Educ_2 | -0.0499*** | -0.0427*** | -0.0357*** |
| | -0.0105 | -0.012 | -0.0102 |
| Educ_3 | -0.0882** | -0.0892** | -0.0777** |
| | -0.0358 | -0.0359 | -0.0333 |
| Educ_4 | -0.117*** | -0.0960*** | -0.0937*** |
| | -0.00768 | -0.00724 | -0.00851 |
| English | 0.0790* | 0.0818** | 0.0799* |
| | -0.0407 | -0.0354 | -0.0392 |
| Constant | 2.383*** | 2.420*** | 2.432*** |
| | -0.0611 | -0.0585 | -0.0634 |
| Observations | 19824 | 21295 | 19816 |
| R-squared | 0.082 | 0.108 | 0.112 |

Notes: Robust standard errors clustered at province level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4 Workplace ban effect, by income groups

| Variables | Lowest income | Low income | Average income | High income | Highest income |
|---|---|---|---|---|---|
| Work Ban | -0.005 | -0.095*** | -0.140*** | -0.107 | -0.215*** |
| | -0.011 | -0.025 | -0.032 | -0.076 | -0.049 |
| Home Ban | -0.189*** | -0.208*** | -0.284*** | -0.258*** | -0.301*** |
| | -0.012 | -0.034 | -0.023 | -0.038 | -0.039 |
| Male | 0.070** | 0.101*** | 0.152*** | 0.251*** | 0.186*** |
| | -0.025 | -0.026 | -0.013 | -0.04 | -0.046 |
| Student | -0.201*** | -0.199*** | -0.297** | -0.483*** | -0.854** |
| | -0.049 | -0.041 | -0.127 | -0.066 | -0.347 |
| Age 20-24 | 0.076*** | 0.05 | -0.037 | 0.045 | 0.136 |
| | -0.019 | -0.04 | -0.108 | -0.108 | -0.169 |
| Age 25-44 | 0.244*** | 0.158** | 0.13 | 0.145 | -0.062 |
| | -0.033 | -0.063 | -0.107 | -0.106 | -0.114 |
| Age 45-64 | 0.340*** | 0.259*** | 0.184 | 0.200* | 0.014 |
| | -0.07 | -0.077 | -0.105 | -0.102 | -0.094 |
| Age 65+ | 0.234*** | 0.048 | -0.093 | 0.261* | 0 |
| | -0.065 | -0.048 | -0.128 | -0.125 | 0 |

Table 4 Workplace ban effect, by income groups (continued)

| Variables | Lowest income | Low income | Average income | High income | Highest income |
|---|---|---|---|---|---|
| Spouse | 0.015 | 0.019 | 0.026 | -0.041 | 0.028 |
| | -0.019 | -0.029 | -0.016 | -0.036 | -0.053 |
| Hhsize | -0.007 | -0.014 | 0.002 | 0.015 | -0.001 |
| | -0.025 | -0.013 | -0.008 | -0.021 | -0.03 |
| Educ_2 | -0.039 | -0.078* | -0.016 | 0.014 | -0.090** |
| | -0.027 | -0.041 | -0.044 | -0.105 | -0.04 |
| Educ_3 | -0.065 | -0.129*** | -0.079 | -0.011 | -0.082 |
| | -0.053 | -0.035 | -0.091 | -0.068 | -0.067 |
| Educ_4 | -0.084*** | -0.130*** | -0.083 | -0.028 | -0.115 |
| | -0.013 | -0.025 | -0.053 | -0.096 | -0.066 |
| Langu2 | 0.071 | 0.143** | 0.025 | 0.039 | 0.093* |
| | -0.055 | -0.064 | -0.044 | -0.039 | -0.048 |
| Constant | 2.375*** | 2.548*** | 2.666*** | 2.594*** | 2.551*** |
| | (−0.088) | (−0.081) | (−0.13) | (−0.087) | (−0.22) |
| Observations | 6472 | 5352 | 4690 | 2564 | 738 |
| R-squared | 0.128 | 0.097 | 0.105 | 0.107 | 0.171 |

Table 5 Workplace ban effect, by education groups

| Variables | < Secondary | Secondary | Some post secondary | College and university |
|---|---|---|---|---|
| Workban | -0.0485 | -0.0828*** | -0.078 | -0.104*** |
| | -0.0347 | -0.0131 | -0.0519 | -0.00935 |
| Homeban | -0.242*** | -0.197*** | -0.238*** | -0.246*** |
| | -0.0258 | -0.0298 | -0.0555 | -0.0274 |
| Male | 0.103*** | 0.119*** | 0.120** | 0.142*** |
| | -0.0159 | -0.0298 | -0.0477 | -0.0077 |
| Income_2 | 0.0574*** | 0.0121 | 0.00228 | 0.0122 |
| | -0.0171 | -0.0283 | -0.0298 | -0.0224 |
| Income_3 | 0.067 | 0.0899** | 0.055 | 0.0531** |
| | -0.0788 | -0.0302 | -0.0568 | -0.0169 |
| Income_4 | 0.0637 | 0.0959** | 0.0992** | 0.0843*** |
| | -0.0911 | -0.0332 | -0.0445 | -0.0207 |
| Income_5 | 0.244*** | 0.155** | 0.216*** | 0.112* |
| | -0.0646 | -0.0609 | -0.066 | -0.0595 |
| English | 0.143** | 0.0972** | 0.0393 | 0.0379 |
| | -0.0514 | -0.0423 | -0.0851 | -0.0504 |

Table 5 Workplace ban effect, by education groups (continued)

| Variables | < Secondary | Secondary | Some post secondary | College and university |
|---|---|---|---|---|
| Age 20-24 | 0.0916** | 0.131*** | 0.0341 | 0.121 |
| | -0.0311 | -0.0309 | -0.0635 | -0.0954 |
| Age 25-44 | 0.216** | 0.292*** | 0.201*** | 0.232* |
| | -0.0814 | -0.0578 | -0.0512 | -0.127 |
| Age 45-64 | 0.194* | 0.358*** | 0.299*** | 0.344** |
| | -0.0899 | -0.0634 | -0.0493 | -0.153 |
| Age 65+ | 0.0193 | 0.299*** | 0.195 | 0.216 |
| | -0.0643 | -0.0602 | -0.136 | -0.143 |
| Spouse | 0.0584* | 0.017 | 0.00434 | -0.00962 |
| | -0.0277 | -0.0175 | -0.0452 | -0.0193 |
| Hhsize | -0.0360** | -0.0116 | -0.00865 | 0.0176 |
| | -0.0158 | -0.0129 | -0.0206 | -0.0127 |
| Student | -0.194** | -0.135* | -0.241*** | -0.248*** |
| | -0.0782 | -0.0612 | -0.0619 | -0.055 |
| Constant | 2.438*** | 2.342*** | 2.569*** | 2.335*** |
| | -0.057 | -0.074 | -0.116 | -0.153 |
| Observations | 5843 | 4351 | 1673 | 7949 |
| R-squared | 0.126 | 0.098 | 0.19 | 0.098 |

Notes: Robust standard errors clustered at province level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Smoking ban effects at different quantiles

| Variables | q20 | q40 | q60 | q75 | q85 | q95 |
|---|---|---|---|---|---|---|
| Workban | -0.028*** | -0.057*** | -0.065*** | -0.061*** | -0.044*** | -0.094*** |
| | -0.001 | -0.009 | -0.022 | -0.019 | -0.013 | -0.01 |
| Homeban | -0.269*** | -0.252*** | -0.249*** | -0.170*** | -0.104*** | -0.124*** |
| | -0.004 | -0.004 | -0.001 | -0.011 | -0.001 | -0.013 |
| Male | 0.191*** | 0.223*** | 0.184*** | 0.121*** | 0.087*** | 0.160*** |
| | -0.003 | -0.012 | -0.006 | -0.001 | -0.007 | -0.004 |
| Income_2 | 0.045*** | 0.034** | 0.015 | 0 | 0.002 | -0.019*** |
| | -0.006 | -0.013 | -0.02 | -0.009 | -0.005 | -0.004 |
| Income_3 | 0.076*** | 0.058*** | 0.037 | 0.008 | 0.004 | -0.01 |
| | -0.018 | -0.013 | -0.025 | -0.018 | -0.012 | -0.009 |
| Income_4 | 0.109*** | 0.095*** | 0.073*** | 0.030* | 0.015*** | -0.002 |
| | -0.009 | -0.007 | -0.024 | -0.016 | -0.003 | -0.019 |
| Income_5 | 0.132*** | 0.130*** | 0.099*** | 0.045** | 0.037*** | 0.085*** |
| | -0.033 | -0.033 | -0.035 | -0.021 | -0.005 | -0.017 |
| Educ_2 | -0.033*** | -0.041** | -0.030*** | -0.030** | -0.030*** | -0.041*** |
| | -0.009 | -0.019 | -0.008 | -0.012 | -0.002 | -0.009 |
| Educ_3 | -0.042** | -0.073*** | -0.070** | -0.038*** | -0.039*** | -0.044 |
| | -0.02 | -0.011 | -0.027 | -0.011 | -0.001 | -0.057 |
| Educ_4 | -0.096*** | -0.109*** | -0.085*** | -0.068*** | -0.051*** | -0.062 |
| | -0.01 | -0.006 | -0.006 | -0.001 | -0.007 | -0.041 |
| Student | -0.240*** | -0.185*** | -0.159*** | -0.186*** | -0.175*** | -0.105*** |
| | -0.052 | -0.049 | -0.013 | -0.011 | -0.011 | -0.032 |

Table 6. Smoking ban effects at different quantiles (continued)

| Variables | q20 | q40 | q60 | q75 | q85 | q95 |
|---|---|---|---|---|---|---|
| Age 20-24 | 0.130*** | 0.117*** | 0.125 | 0.114 | 0.083 | 0.051 |
| | -0.004 | -0.035 | -0.08 | -0.073 | -0.052 | -0.042 |
| Age 25-44 | 0.335*** | 0.305*** | 0.328*** | 0.341*** | 0.198*** | 0.128*** |
| | -0.056 | -0.003 | -0.03 | -0.031 | -0.008 | -0.034 |
| Age 45-64 | 0.394*** | 0.427*** | 0.458*** | 0.401*** | 0.254*** | 0.231*** |
| | -0.038 | 0 | -0.038 | -0.032 | -0.002 | -0.006 |
| Age 65+ | 0.192*** | 0.202*** | 0.279*** | 0.280*** | 0.179*** | 0.119*** |
| | -0.031 | -0.058 | -0.06 | -0.046 | -0.007 | -0.023 |
| Spouse | 0.026*** | 0.011 | -0.013*** | -0.008** | -0.015** | -0.026 |
| | -0.001 | -0.012 | -0.004 | -0.004 | -0.007 | -0.019 |
| Hhsize | 0.002 | 0.006*** | 0.011*** | 0 | 0.007** | -0.005 |
| | -0.004 | 0 | -0.002 | 0 | -0.003 | -0.006 |
| English | 0.039*** | 0.038*** | 0.033*** | 0.030*** | 0.024*** | 0.011*** |
| | -0.007 | -0.008 | -0.007 | -0.002 | -0.005 | 0 |
| Constant | 1.867*** | 2.246*** | 2.509*** | 2.742*** | 2.996*** | 3.355*** |
| | -0.035 | -0.002 | -0.027 | -0.021 | -0.016 | -0.012 |
| Obs | 19816 | 19816 | 19816 | 19816 | 19816 | 19816 |

Notes: Robust standard errors clustered at province level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7. IV Estimation of Home Ban Effects

| Variables | IV=Children | IV=Member | IV=Children &Member 2SLS | IV=Children &Member GMM | IV=Children &Member LIML |
|---|---|---|---|---|---|
| Homeban | -0.391*** | -0.292* | -0.366*** | -0.356*** | -0.366*** |
| | -0.082 | -0.172 | -0.077 | -0.084 | -0.077 |
| Workban | -0.074*** | -0.079*** | -0.076*** | -0.076*** | -0.076*** |
| | -0.014 | -0.022 | -0.016 | -0.018 | -0.016 |
| Male | 0.130*** | 0.128*** | 0.130*** | 0.130*** | 0.130*** |
| | -0.009 | -0.011 | -0.009 | -0.009 | -0.009 |
| Age 20-24 | 0.078*** | 0.076*** | 0.075** | 0.075** | 0.075** |
| | -0.027 | -0.028 | -0.03 | -0.03 | -0.03 |
| Age 25-44 | 0.207*** | 0.208*** | 0.201*** | 0.202*** | 0.201*** |
| | -0.039 | -0.028 | -0.038 | -0.036 | -0.038 |
| Age 45-64 | 0.270*** | 0.279*** | 0.269*** | 0.271*** | 0.269*** |
| | -0.051 | -0.034 | -0.046 | -0.043 | -0.046 |
| Age 65+ | 0.124*** | 0.128*** | 0.119*** | 0.120*** | 0.119*** |
| | -0.043 | -0.021 | -0.035 | -0.033 | -0.035 |
| Educ_2 | -0.026** | -0.031*** | -0.026*** | -0.027*** | -0.026*** |
| | -0.012 | -0.01 | -0.01 | -0.009 | -0.01 |
| Educ_3 | -0.070** | -0.075** | -0.072** | -0.072** | -0.072** |
| | -0.031 | -0.036 | -0.031 | -0.031 | -0.031 |
| Educ_4 | -0.078*** | -0.091*** | -0.084*** | -0.084*** | -0.084*** |
| | -0.013 | -0.011 | -0.008 | -0.008 | -0.008 |

Table 7. IV Estimation of Home Ban Effects (continued)

| Variables | IV=Children | IV=Member | IV=Children &Member 2SLS | IV=Children &Member GMM | IV=Children &Member LIML |
|---|---|---|---|---|---|
| Income_2 | 0.020** | 0.024*** | 0.023*** | 0.023*** | 0.023*** |
| | -0.01 | -0.008 | -0.009 | -0.009 | -0.009 |
| Income_3 | 0.066** | 0.066** | 0.067** | 0.066*** | 0.067** |
| | -0.027 | -0.026 | -0.026 | -0.026 | -0.026 |
| Income_4 | 0.098*** | 0.096*** | 0.100*** | 0.099*** | 0.100*** |
| | -0.02 | -0.02 | -0.02 | -0.02 | -0.02 |
| Income_5 | 0.155*** | 0.155*** | 0.158*** | 0.156*** | 0.158*** |
| | -0.048 | -0.038 | -0.043 | -0.041 | -0.043 |
| Student | -0.207*** | -0.221*** | -0.216*** | -0.216*** | -0.216*** |
| | -0.044 | -0.056 | -0.05 | -0.05 | -0.05 |
| Constant | 2.468*** | 2.458*** | 2.474*** | 2.470*** | 2.474*** |
| | -0.063 | -0.03 | -0.052 | -0.044 | -0.052 |
| Observations | 19816 | 19594 | 19594 | 19594 | 19594 |
| R-squared | 0.098 | 0.11 | 0.101 | 0.103 | 0.101 |
| First stage F | F(1,10) =227 | F(1,10) =29 | F(2,10) =185 | F(2,10) =185.58 | F(2,10) =185.58 |
| Overidentify | | | Score = 0.49 | Hansen's J = .18 | A-R = .47 |
| Restriction test | | | (p = 0.48) | (p = 0.67) | (p = 0.48) |

Notes: Robust standard errors clustered at province level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Regression controls for spouse, household size and English language.

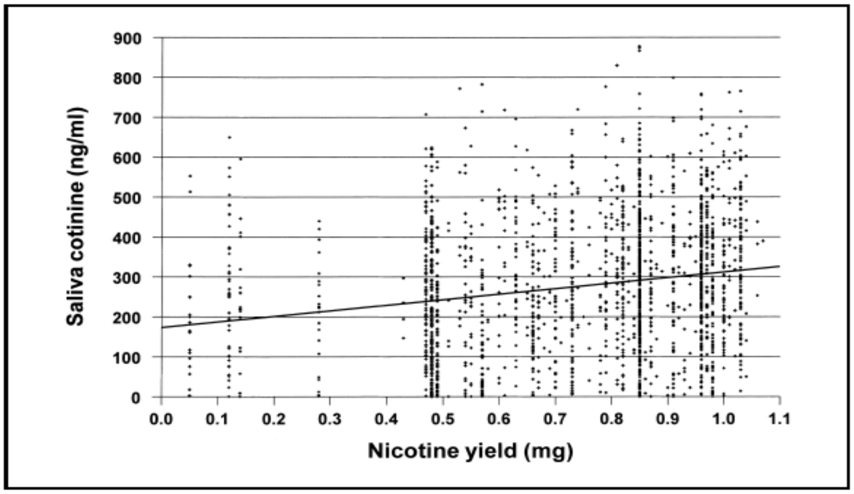


Figure 1. Cotinine levels as a function of cigarette strength (Jarvis *et al*, 2001)

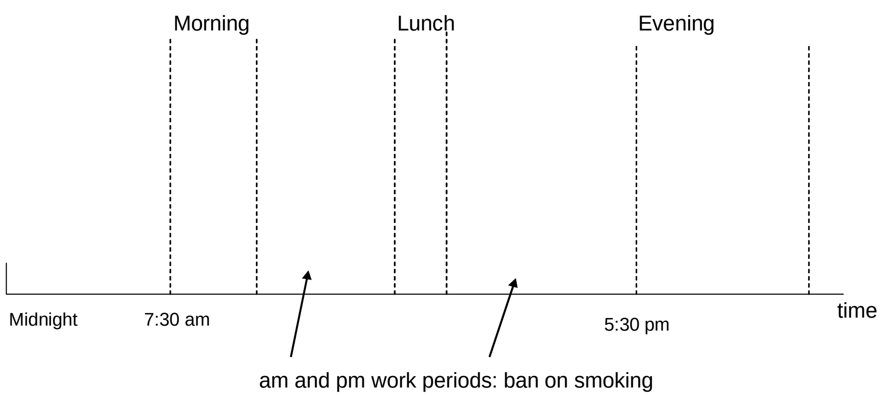


Figure 2. Daily restricted and unrestricted periods

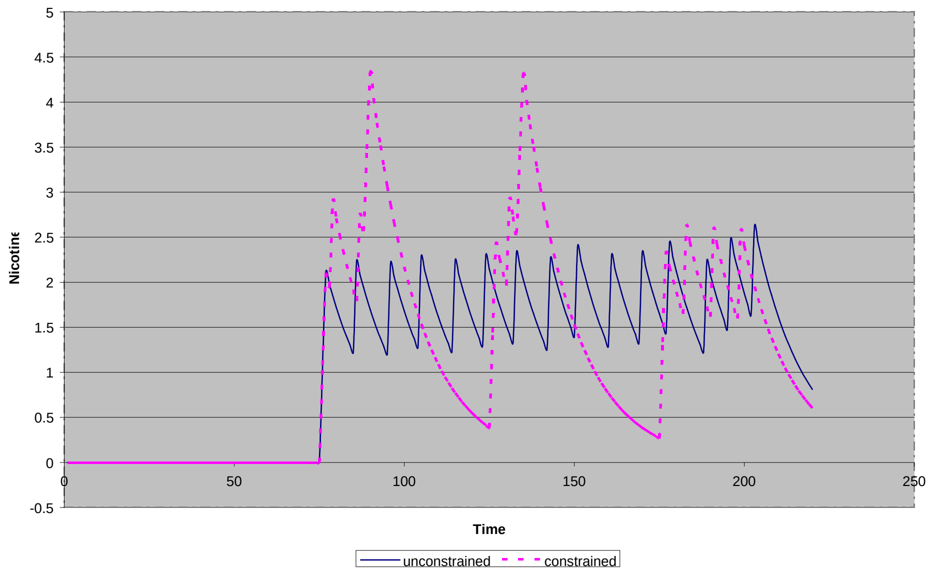


Figure 3. Optimal nicotine patterns for 16 cigarettes

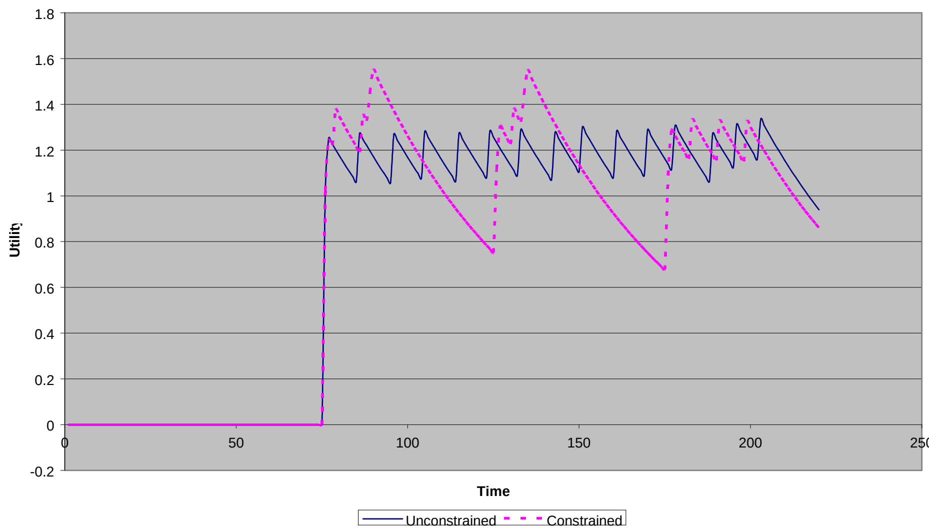


Figure 4. Utility path for optimal consumption pattern of 16 cigarettes

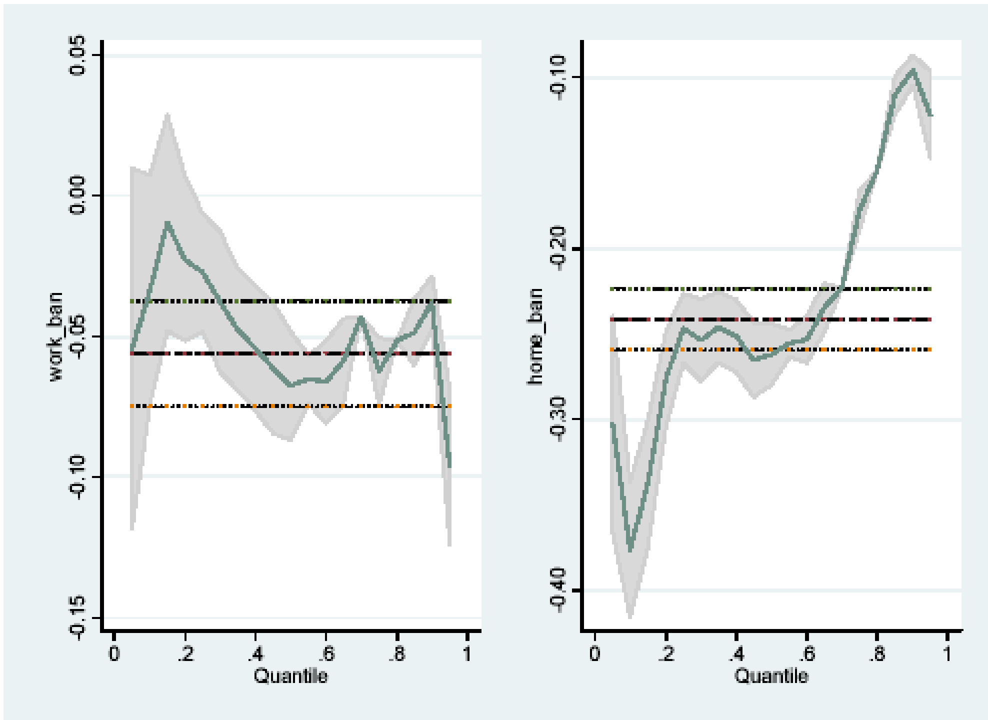


Figure 5. Workplace and home bans by quantile of smokers.